Army Research Laboratory

RoboLeader: A Surrogate for Enhancing the Human Control of a Team of Robots

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ARL-MR-0735 **February 2010**

NOTICES

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Army Research Laboratory
Adelphi, MD 20783-1197

ARL-MR-0735 **February 2010**

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REPORT DOCUMENTATION PAGE

Form Approved
OMB No. 0704-0188

1. REPORT DATE *(DD-MM-YYYY)*	2. REPORT TYPE	3. DATES COVERED (From - To)
February 2010	DRI	

4. TITLE AND SUBTITLE
RoboLeader: A Surrogate for Enhancing the Human Control of a Team of Robots

5a. CONTRACT NUMBER

5b. GRANT NUMBER

5c. PROGRAM ELEMENT NUMBER

6. AUTHOR(S)
Jessie Y.C. Chen, Michael J. Barnes, and Zhihua Qu

5d. PROJECT NUMBER

5e. TASK NUMBER

5f. WORK UNIT NUMBER

7. PERFORMING ORGANIZATION NAME(S) AND ADDRESS(ES)
U.S. Army Research Laboratory
ATTN: RDRL-HRM-AT
2800 Powder Mill Road
Adelphi, MD 20783-1197

8. PERFORMING ORGANIZATION REPORT NUMBER
ARL-MR-0735

9. SPONSORING/MONITORING AGENCY NAME(S) AND ADDRESS(ES)

10. SPONSOR/MONITOR'S ACRONYM(S)

11. SPONSOR/MONITOR'S REPORT NUMBER(S)

12. DISTRIBUTION/AVAILABILITY STATEMENT
Approved for public release; distribution unlimited.

13. SUPPLEMENTARY NOTES

14. ABSTRACT
RoboLeader, an intelligent agent, was developed to assist human operators in controlling a team of unmanned vehicles through route planning tasks. Though there were no significant differences between the RoboLeader and baseline conditions in target detection, the RoboLeader group reduced their mission completion times by approximately 13% compared to the baseline group. Operators’ target detection performance in the four- and eight-vehicle conditions were analyzed, with results showing significantly fewer targets identified in the eight-vehicle condition compared to the four-vehicle condition. Participants with higher spatial ability detected more targets than those with lower spatial ability. Participants experienced significantly higher workload in the eight-vehicle condition compared to the four-vehicle condition. Participants with better attentional control reported lower workload than those with poorer attentional control, and females reported significantly higher workload than males.

15. SUBJECT TERMS
Supervisory control; automation; intelligent agent; reconnaissance; individual differences; simulation

16. SECURITY CLASSIFICATION OF:			17. LIMITATION OF ABSTRACT	18. NUMBER OF PAGES	19a. NAME OF RESPONSIBLE PERSON
a. REPORT	b. ABSTRACT	c. THIS PAGE			Jessie Y.C. Chen
Unclassified	Unclassified	Unclassified	UU	20	19b. TELEPHONE NUMBER (*Include area code*) (407) 384-5435

Standard Form 298 (Rev. 8/98)
Prescribed by ANSI Std. Z39.18

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1. Objective

Unmanned vehicles (UV) are being used more frequently in military operations, and the types of tasks they are being used for are evolving in complexity. In the future battlefield, Soldiers may be given multiple tasks to perform concurrently, such as navigating a UV while conducting surveillance, maintaining local security and situational awareness (SA), and communicating with fellow team members. In order to maximize human resources, it is desirable to designate a single operator to supervise multiple UVs simultaneously. However, past research has shown that human operators are often unable to control multiple robots/agents simultaneously in an effective and efficient manner (*1, 2*). Additionally, as the size of the robot team increases, the human operators may fail to maintain adequate SA when their attention has to constantly switch among the robots, and their cognitive resources may be overwhelmed by intervention requests from the robots (*3, 4*). Wang et al. (*4*) reviewed a number of studies on supervisory control of multiple ground robots for target detection tasks and concluded that “the fan-out plateau lies somewhere between 4 and 9+ robots depending on the level of robot autonomy and environmental demands” (p. 143).

Research showed that autonomous cooperation between robots can aid the performance of the human operators (*3*) and enhance the overall human-robot team performance (*2*). Wang et al. (*4*) suggest that automating navigation-related tasks (e.g., path-planning) is more important than “efforts to improve automation for target recognition and cueing” (p.146) in the context of controlling a large team of robots. However, in the foreseeable future, human operators’ involvement in mixed-initiative (i.e., human-robot) teams will always be required, especially for critical decision making. Human operators’ decision making may be influenced by “implicit goals” that the robots are not aware of (i.e., are not programmed into the behaviors of the robots) (*5*). In addition, the real-time development on the battlefield may require the human operator to change the plan for the robot team and/or the individual robots. Therefore, effective communication between the human operator and the robots is critical in ensuring mission successes. Research has been conducted on ways to enhance human-robot communication (*6*). For example, researchers at Carnegie Mellon University demonstrated the effectiveness of a robot proxy to enhance shared understanding between the human operator and the robot in an exploration task (*6*). The communication mechanism was based on a common ground collaboration model and was able to improve the human operator performance in the following areas: more accurate plans, more efficient planning (fewer planning repetitions), more efficient and faster task performance, and better mental model of the capabilities of the robot (*6*).

In the current study, we investigated whether RoboLeader, a robotic surrogate for the human operator and an intelligent agent that can interpret the operator’s intent and issue detailed command signals to a team of robots of lower capabilities, could enhance the overall human-robot teaming performance. With the RoboLeader capabilities, dependence on operator instructions was reduced and the level of autonomy in operating UVs was improved by implementing such algorithms as real-time path planning, cooperative control, and multi-objective decision of tactical strategies. These algorithms were stacked and the operator only needed to make high-level decisions (*7–11*). These algorithms resided in RoboLeader and enabled the operator to control a team of robots through a single user interface. RoboLeader was able to assess the feasibility of the operator's plans by simulating their execution.

The effects of individual differences factors on operator performance were also evaluated. More specifically, we investigated the effects of individual differences in spatial ability (SpA) and perceived attentional control (PAC) on the operators' robotics control as well as multitasking performance. Previous research has demonstrated that SpA is a good predictor of the operator's robotics performance (*1, 12*). In the current study, we also examined the relationship between attentional control and multitasking performance. Several studies show that there are individual differences in multitasking performance, and some people are less prone to performance degradation during multitasking conditions (*13*). There is evidence that people with better attentional control can allocate their attention more flexibly and effectively (*14*), and this was partially confirmed by Chen and Joyner (*15*).

2. Approach

2.1 Participants

Thirty individuals (17 males and 13 females, with a mean age of 24.73 years) from the Orlando, FL, area participated in the study. They were compensated $15/h for their time.

2.2 Apparatus: Simulator and RoboLeader Algorithm

The Mixed Initiative Experimental (MIX) Testbed was modified and used as the simulator (*16*). The Operator Control Unit (OCU) of the MIX Testbed was modeled after the Tactical Control Unit developed under the U.S. Army Research Laboratory (ARL) Robotics Collaborative Technology Alliance (figure 1). The path generator designed and implemented within the MIX Testbed was designed for maximum search efficiency, and using simple concepts from vector mechanics, a unique behavior was given to the planning characteristics of the path generator that stands out from typical matrix search algorithms. Using vector mechanics, the path generator can be given a start point and an endpoint to navigate toward and the algorithm will "home in" on the intended destination. The path generator has the ability to wrap around the destination until an entry path is found.

Figure 1. RoboLeader interface.

2.3 Surveys and Tests

A demographics questionnaire was administered at the beginning of the training session. An Ishihara color vision test (with nine test plates) was administered via PowerPoint® presentation. The RoboLeader user interface employed several colors to display the plans for the robots and normal color vision was required to effectively interact with the system. A questionnaire on Attentional Control (*14*) was used to evaluate participants' perceived attentional control. The Attentional Control survey consists of 21 items and measures attention focus and shifting. The scale has been shown to have good internal reliability ($\alpha = 0.88$). The Cube Comparison Test (*17*) and Spatial Orientation Test (*18*) were used to assess participants' SpA. The Cube Comparison Test required participants to compare, in 3 min, 21 pairs of 6-sided cubes and determine if the rotated cubes were the same or different. The Spatial Orientation Test, modeled after the cardinal direction test developed by Gugerty and his colleagues (*18*), is a computerized test consisting of a brief training segment and 32 test questions. Both accuracy and response time were automatically captured by the program. Participants' perceived workload was evaluated using the computerized version of National Aeronautics and Space Administration Task Load Index (NASA-TLX) questionnaire, using a pairwise comparison weighting procedure (*19*). The NASA-TLX is a self-reported questionnaire of perceived demands in six areas: mental, physical, temporal, effort (mental and physical), frustration, and performance. Participants evaluated their perceived workload level in these areas on 10-point scales as well as completed pairwise comparisons for each subscale.

2.4 Procedure

Participants were randomly assigned to the RoboLeader group or the baseline (no RoboLeader) group. After the informed consent form process, participants completed the demographic questionnaire and the Attentional Control survey, and were administered a brief Ishihara color vision test and two spatial ability tests. After the spatial tests, participants received training, which lasted about 1 h and was self-paced, delivered by PowerPoint slides showing the elements of the OCU user interface, steps for completing various tasks, and several mini-exercises for practicing the steps. Each experimental session had two scenarios, each lasting approximately 30 min, in which participants used their robotic assets to locate 10 targets (i.e., insurgents carrying weapons) in the remote environment. There were four robots available in one scenario and eight robots in the other scenario. The order of scenarios was counterbalanced across participants. The experimental session lasted about 1 h.

When each scenario started, the robots began by following pre-planned routes, at which time the operator's task of monitoring the environment and detecting insurgents/improvised explosive devices (IEDs) began. The robots did not have Aided Target Recognition (AiTR) capability; therefore, the participants had to detect the 10 insurgents and 10 IEDs themselves. For the insurgents, participants were instructed to use their computer mouse to click on the targets to "lase" them as soon as they were detected. The "lased" insurgents were automatically displayed on the map. For the IEDs, the participants clicked on the IED button on the interface, and then marked the locations of the IEDs on the map. Additionally, there were friendly dismounted Soldiers and civilians in the simulated environment to increase the visual noise for the target detection tasks. The participants were told that their objective was to finish reconnoitering the area using their robotic assets in the least amount of time possible. Therefore, when re-planning a route, the participant and/or RoboLeader must consider both the effectiveness and efficiency of the new route. Situations where a robot completed its route quickly but did not cover much ground, or where the robot covered a lot of ground but was slow to finish, were considered suboptimal in comparison to re-planning a route that efficiently (i.e., less time) covered a lot of ground. RoboLeader would recommend new routes for robots that finished first, if it decided that the overall mission time could be reduced by redirecting those robots to the unsearched areas.

In each scenario, there were six events that required revisions to a robot's current plans/route. Once an event transpired, the baseline participants had to notice that the event had occurred (via an auditory alert) and then re-route the robot that was affected by the event. For those in the RoboLeader condition, the RoboLeader would recommend plan revisions to the operator, who could either accept the plans or modify them as necessary. Out of these six events, three were "bottom-up" (e.g., unanticipated obstacles detected by the robots that obstruct their navigation) and three "top-down" (e.g., intel that the human operator receives from the intel network). Given that the events led to obstructions (e.g., vehicles in the path, hostile area), the RoboLeader and the participants needed to avoid re-routing through these areas, in addition to avoiding areas where insurgents or IEDs were already detected.

In each scenario, there were five SA queries, which were triggered based on time progression (e.g., 3 min into the scenario). The SA queries included questions such as "which areas have the robots searched?" (the participant marked the searched areas on a blank map), "which of your robots is the closest to [Area of Interest]," etc. The OCU screen was blank when an SA query was triggered, and only the SA queries were displayed on the screen.

There were 2-min breaks between experimental sessions. Participants assessed their perceived workload (NASA-TLX) after each experimental scenario.

The study was a mixed design, with RoboLeader (with or without RoboLeader [baseline]) as the between-subject variable, and the number of robots used in the scenario (four vs. eight) the within-subject variable. Performance measures included number of targets located and identified, the operator's SA of the mission environment, as well as awareness of the status of the individual robots. A mixed-design analysis of covariance (ANCOVA) with RoboLeader (with or without RoboLeader) as the between-subject factor and number of robots (four vs. eight) as the within-subject factor was used to evaluate the operator's performance differences among the four conditions. Participants' SpA (composite score of the two spatial tests) and their attentional control survey scores were used as covariates.

3. Results

3.1 Target Detection Performance

The analysis revealed that the robots' condition significantly affected the number of targets detected, $F(1,26) = 21.72$, $p < 0.0001$. Participants detected significantly fewer insurgents when they had eight robots compared with the condition when four robots were available. Participants with a higher SpA detected significantly more insurgents than those with a lower SpA did, $F(1,26) = 6.63$, $p < 0.05$ (figure 2). The effects of RoboLeader and attentional control were not statistically significant. The analysis also showed that participants detected significantly fewer IEDs when they had eight robots compared with the condition when four robots were available, $F(1,26) = 10.13$, $p < 0.005$. Participants with a higher SpA detected significantly more insurgents than those with a lower SpA did, $F(1,26) = 10.66$, $p < 0.005$ (figure 3). The effects of RoboLeader and attentional control were not statistically significant. There was a non-significant RoboLeader x SpA effect, $F(1,26) = 2.55$, $p = 0.12$. As can be seen in figure 3, participants with a higher SpA performed slightly better with RoboLeader compared with the baseline condition; however, the same pattern was not observed for the lower SpA group.

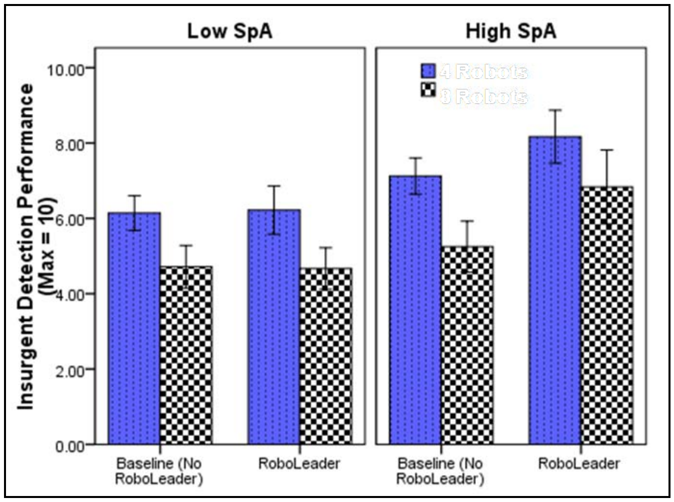

Figure 2. Insurgent detection performance.

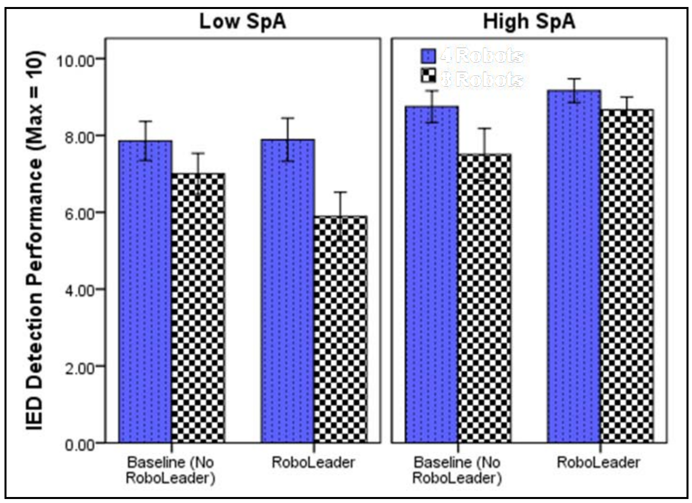

Figure 3. IED detection performance.

3.2 SA Queries

The analysis revealed that participants' SA was significantly lower when they had eight robots compared with the condition when four robots were available, $F(1,26) = 13.31$, $p < 0.005$. None of the other factors were significant (figure 4).

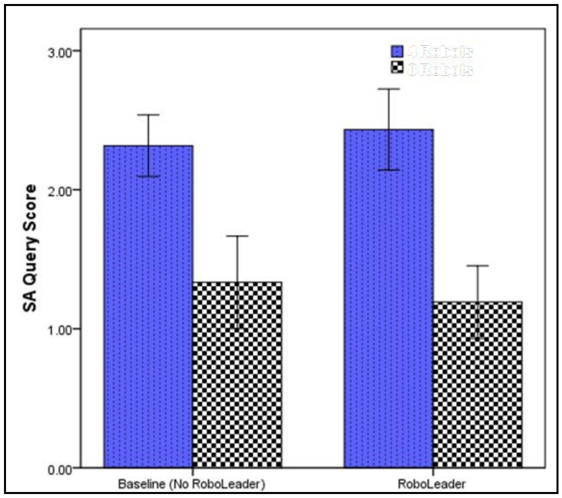

Figure 4. Situation awareness.

3.3 Perceived Workload

The analysis showed that participants experienced significantly higher workload when there were eight robots (M = 69.3) vs. four robots (M = 64.3), $F(1,26) = 4.95$, $p < 0.05$ (figure 5). Participants in the RoboLeader group assessed their workload slightly lower (M = 64.11) than those in the baseline group (M = 69.4) did. However, the difference failed to reach statistical significance. Participants with higher attentional control rated their workload as significantly lower than those with lower attentional control did, $F(1,26) = 7.23$, $p < 0.05$. Notably, females reported significantly higher workload (4-robot: 74.97; 8-robot: 77.05) than males (4-robot: 56.18; 8-robot: 63.29) did, $F(1,28) = 12.16$, $p < 0.005$.

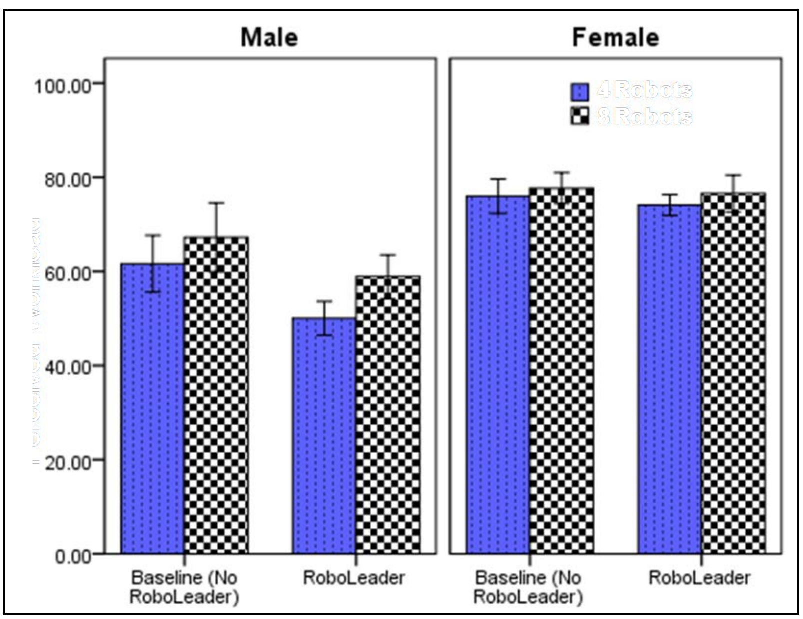

Figure 5. Perceived workload.

3.4 Operators' Interaction with the OCU

Participants' interaction with the OCU (e.g., clicks on the graphical user interface [GUI]) was further analyzed. Overall, participants in the RoboLeader spent significantly less time completing their mission scenarios than did those in the baseline group, $F(1,27) = 7.12$, $p < 0.05$. Participants in the RoboLeader group spent, on average, 20.7 min per scenario; while, those in the baseline group spent 23.8 min per scenario. During the experiment, participants needed to click on the smaller thumbnails (i.e., streaming videos from the robots) to enlarge the video image in order to identify targets. Participants in the baseline group made significantly more clicks on the thumbnails than those in the RoboLeader group did, $F(1,25) = 8.33$, $p < 0.01$. They also made more clicks when they had eight robots compared with the four-robot condition, $F(1,25) = 132.23$, $p < 0.001$. Additionally, there was a significant RoboLeader x Robots interaction, $F(1,25) = 5.09$, $p < 0.05$ (figure 6). The difference between the baseline and the RoboLeader groups was greater in the eight-robot condition than that in the four-robot condition.

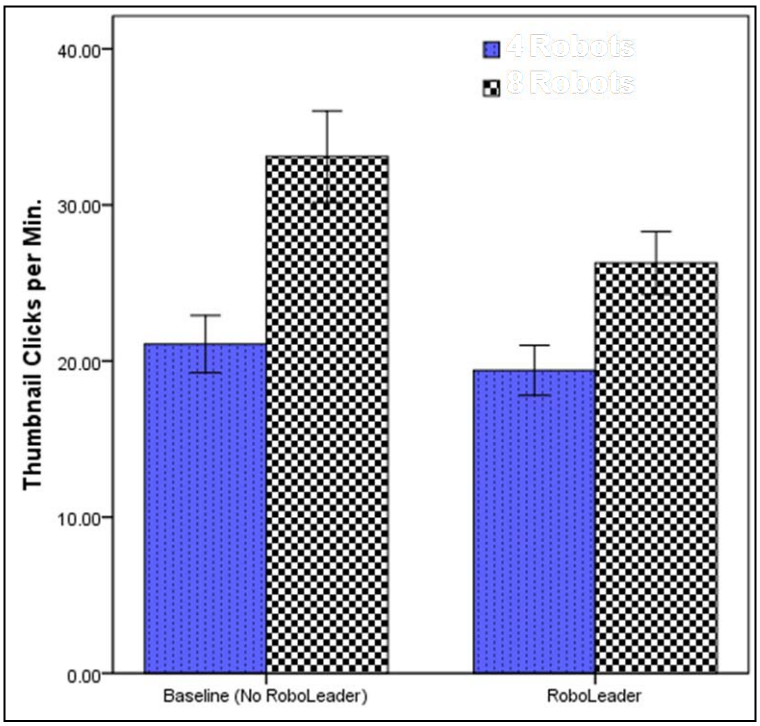

Figure 6. Thumbnail clicks per minute.

4. Conclusions

An intelligent agent, RoboLeader, was developed to assist operators in controlling a team of robots in route planning tasks. Although no significant differences were found in target detection between the groups, the RoboLeader group completed their missions in significantly less time than those in the baseline group. On average, RoboLeader saved the participants ~3 min for missions lasting 20+ min. While this finding was expected given the assistance from RoboLeader in route planning tasks, participants in the RoboLeader group exhibited more pronounced complacency in the eight-robot condition compared to the baseline group. More specifically, the RoboLeader participants made fewer clicks on thumbnails of the streaming video from the robots (to look for targets) in the eight-robot condition. While the number of clicks did not directly translate into higher number of targets detected, the striking difference in the way the operators interacted with the OCU based on the presence of RoboLeader requires further investigation.

We compared the operators' target detection performance in four- and eight-robot conditions. The results showed that the participants detected significantly fewer insurgents and IEDs when there were eight robots compared to the four-robot condition, indicating *less* effectiveness with *more* resources/assets. Those participants with higher SpA detected more insurgents as well as IEDs. These results are consistent with previous findings that individuals with a higher SpA tend to exhibit more effective scanning performance and, therefore, are able to detect more targets than individuals with a lower SpA (*1, 15*). It is likely that RoboLeader's utility was not sufficient to overcome the effect of SpA. In other words, the participants with higher SpA were able to outperform those with lower SpA, regardless of the RoboLeader condition.

When there were eight robots, the participants' SA was significantly worse than when there were four robots. On the other hand, the SA of the RoboLeader participants was not significantly degraded compared with the baseline group. In other words, the out-of-the-loop phenomenon associated with automation (*15*) was not manifest in the RoboLeader condition.

Finally, participants experienced significantly higher workload when there were eight robots compared to the four-robot condition, and those with better attentional control reported lower workload than did those with poorer attentional control. Females also reported significantly higher workload than males did. Those participants in the RoboLeader group rated their workload as slightly lower than those in the baseline group did, although the difference did not reach statistical significance.

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6. Transitions

RoboLeader will be used to support our year two Director's Research Initiative (DRI) research in which the capabilities of RoboLeader will be expanded to deal more specifically with dynamic re-tasking requirements for persistent surveillance of a simulated urban environment based on various battlefield developments (e.g., individual robots need to be re-tasked to search for a high-stakes target). Furthermore, the capability of RoboLeader will be extended beyond coordination with homogeneous assets (i.e., unmanned ground vehicles [UGVs]) to coordination with heterogeneous assets (i.e., unmanned aerial vehicles [UAVs] and UGVs) when in pursuit of moving targets in urban environments. Additionally, RoboLeader will be used for studies of automation reliability and operator individual differences in future Safe Operations for Unmanned Reconnaissance in Complex Environments (SOURCE) Army Technology Objective (ATO) research.

A technical report is being prepared, as well as papers for submission at conferences on robotics and human-robot interaction.

List of Symbols, Abbreviations, and Acronyms

AiTR	Aided Target Recognition
ANCOVA	analysis of covariance
ARL	U.S. Army Research Laboratory
ATO	Army Technology Objective
DRI	Director's Research Initiative
GUI	graphical user interface
IEDs	improvised explosive devices
MIX	Mixed Initiative Experimental
NASA-TLX	National Aeronautics and Space Administration Task Load Index
OCU	Operator Control Unit
PAC	perceived attentional control
SA	situational awareness
SOURCE	Safe Operations for Unmanned Reconnaissance in Complex Environments
SpA	spatial ability
UAVs	unmanned aerial vehicles
UGVs	unmanned ground vehicles
UV	unmanned vehicles

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